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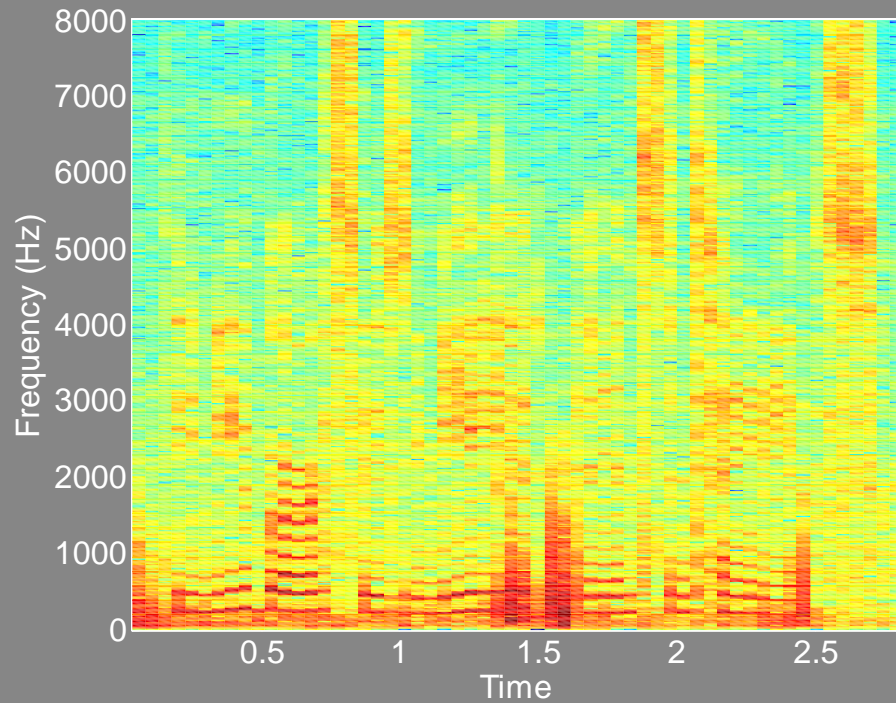
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# Wind Noise Reduction Using Non-negative Sparse Coding

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Wind Noise  
Reduction  
System



available



# The spectrum of alternative methods

- Wiener filter (Wiener, 1949)
- Spectral subtraction (Boll 1979; Berouti et al. 1979)
- AR codebook-based spectral subtraction (Kuropatwinski & Kleijn 2001)
- Minimum statistics (Martin et al. 2001, 2005)
- Masking techniques (Wang; Weiss & Ellis 2006)
- Factorial models (Roweis 2000, 2003)
- MMSE (Radfar & Dansereau, 2007)
- Non-negative sparse coding (Schmidt & Olsson 2006)



## Noise Reduction

Estimate the speaker,  $s(t)$ , given a noisy recording  $x(t)$

$$x(t) = s(t) + n(t)$$

... based on prior knowledge of the noise,  $n(t)$

# Single Channel Source Separation

Hard problem: There is no spatial information

- we cannot use
  - Beamforming
  - Independent component analysis





# Signal Representation

## ■ Exponentiated magnitude spectrogram

$$X = |\text{STFT}\{x(t)\}|^\gamma$$

$\gamma = 2$       Power spectrogram

$\gamma = 1$       Magnitude spectrogram

$\gamma = 0.67$       Cube root compression

(Steven's power law - perceived intensity)

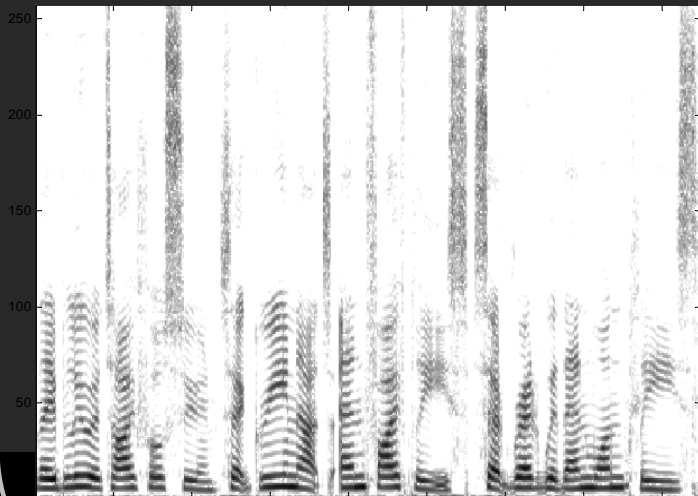
## ■ Ignore phase information. Reconstruct by re-filtering

# Non-negative Sparse Coding

- Factorize the signal matrix

$$X \approx DH$$

Spectrogram



Dictionary



$\approx$

$\times$

Sparse Code







# Non-negative Sparse Coding

- Factorize the signal matrix

$$X \approx DH$$

where  $D$  and  $H$  are non-negative and  $H$  is sparse

- **Non-negativity**: Parts-based representation, only additive and not subtractive combinations
- **Sparseness**: Only few dictionary elements active simultaneously. Source specific and more unique.



# The Dictionary and the Sparse Code

$$X \approx DH$$

## ■ Dictionary, $D$

- Source dependent over-complete basis
- Learned from data



## ■ Sparse Code, $H$

- Time & amplitude for each dictionary element
- Sparseness: Only a few dictionary elements active simultaneously





# Non-negative Sparse Coding of Noisy Speech

- Assume sources are additive

$$X = X_s + X_n \approx [D_s \ D_n] \begin{bmatrix} H_s \\ H_n \end{bmatrix} = DH$$



# Permutation Ambiguity

$$X \approx [D_s \ D_n] \begin{bmatrix} H_s \\ H_n \end{bmatrix} = DH = (DP)(P^\top H)$$

- Precompute both dictionaries (Schmidt & Olsson 2006)
  - Devise a grouping rule (Wang & Plumbley 2005)
  - Precompute wind dictionary and learn speech dictionary from noisy recording
  - Use multiplicative update rule (Eggert&Körner 2004)
- Other rules could be used e.g. projected gradient (Lin, 2007)



# Importance and sensitivity of parameters

## ■ Representation

- STFT exponent

## ■ Sparseness

- Precomputed wind noise dictionary
- Wind noise
- Speech

## ■ Number of dictionary elements

- Wind noise
- Speech

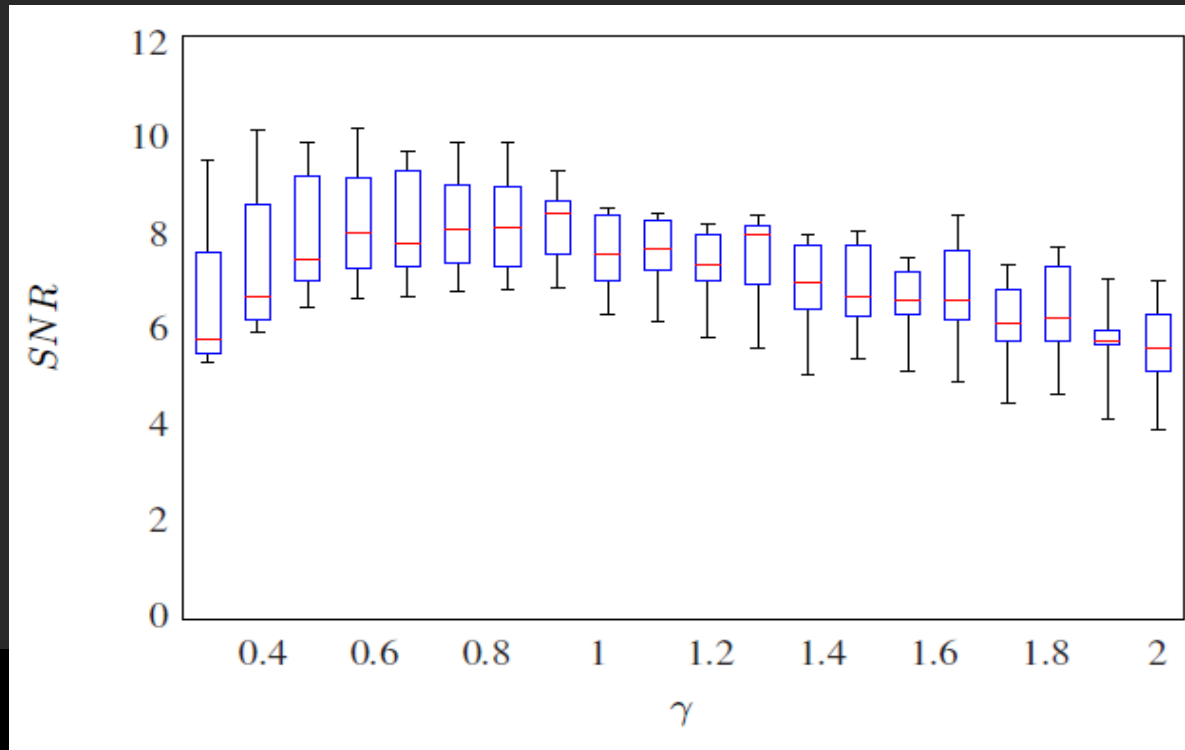


# Quality Measure

- Signal to noise ratio
  - Simple measure, has only indirect relation to perceived quality
- Representation-based metrics
  - In systems based on time-frequency masking, evaluate the masks
- Perceptual models
  - Promising to use PEAQ or PESQ
- High-level Attributes
  - For example word error rate in a speech recognition setup
- Listening-tests
  - Expensive, time-consuming, aspects (comfort, intelligibility)

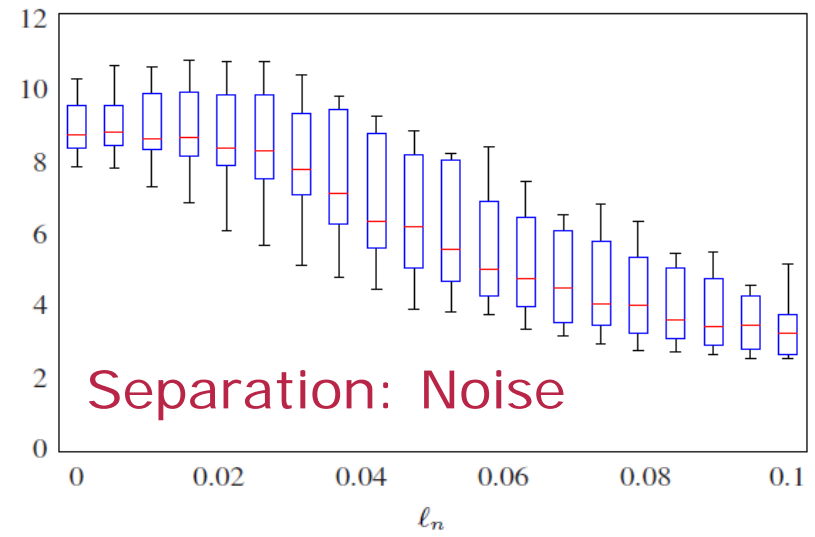
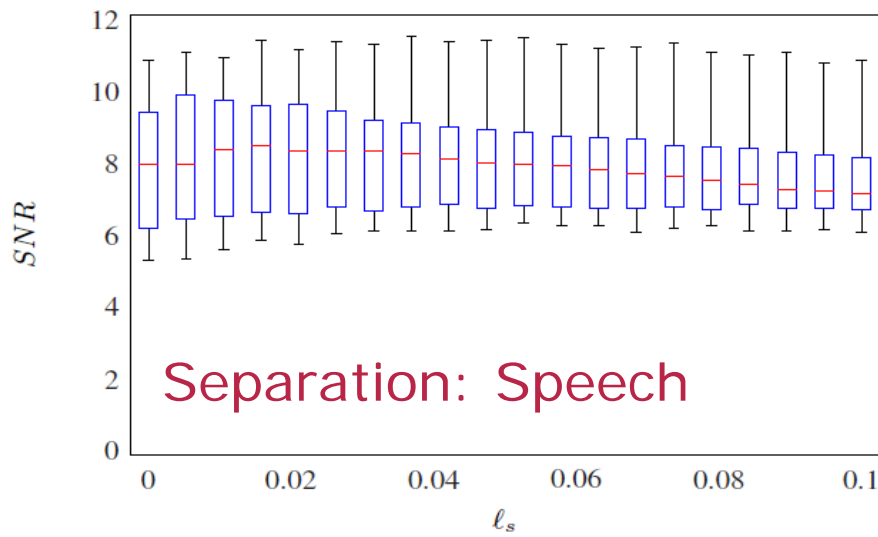
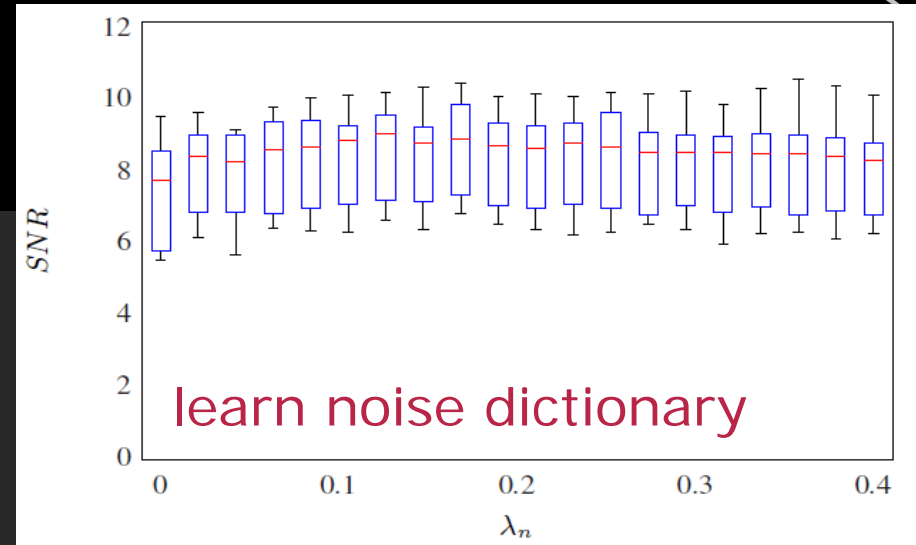
# Signal Representation

## ■ Exponentiated magnitude spectrogram



# Sparseness

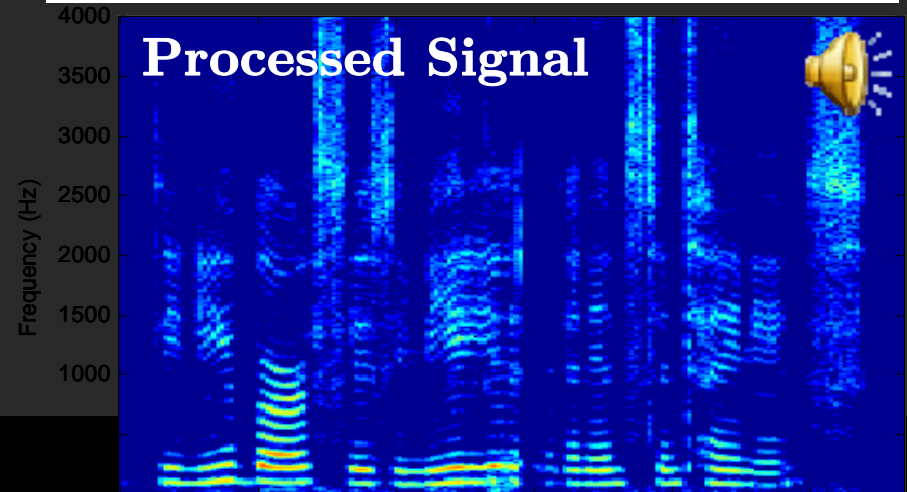
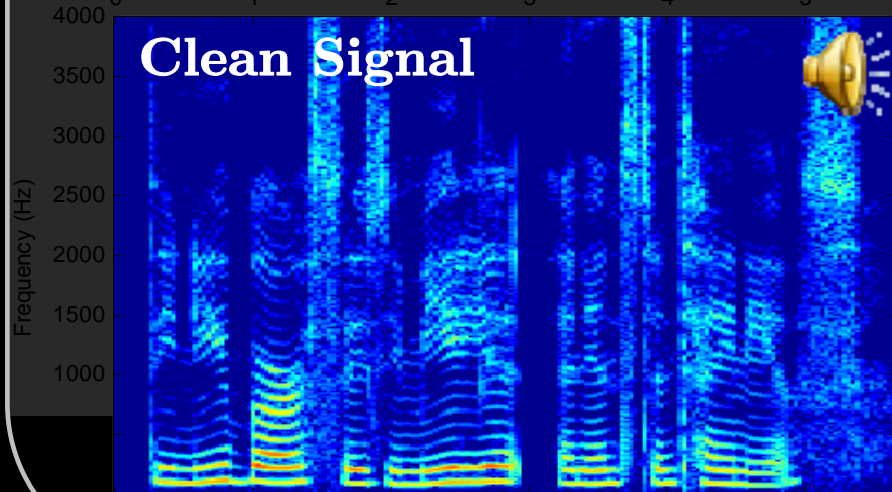
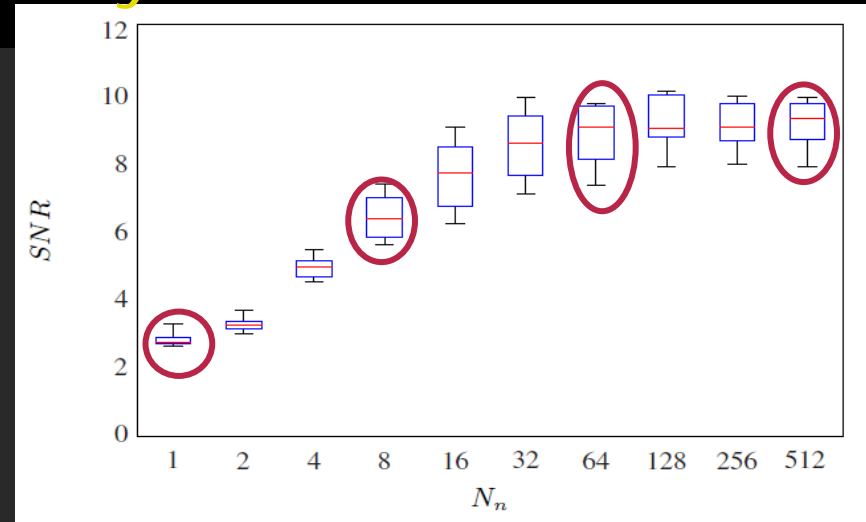
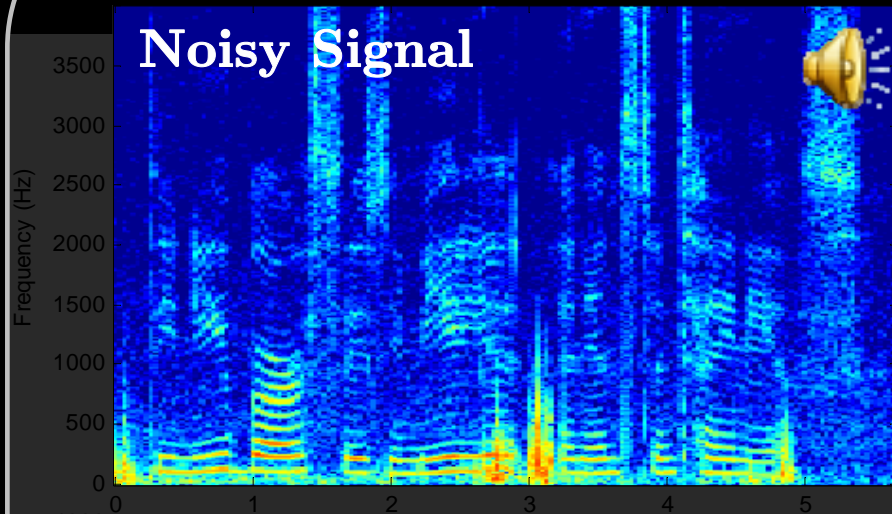
**Qualitatively:** Tradeoff between residual noise and speech distortion





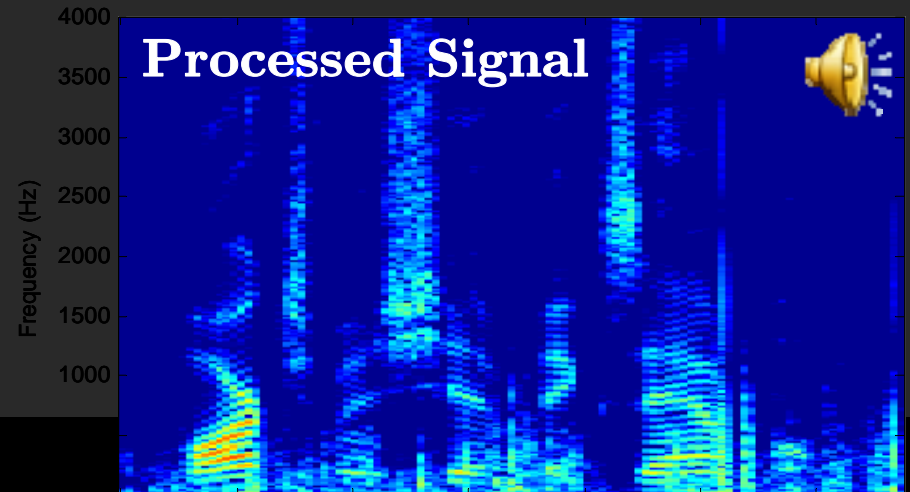
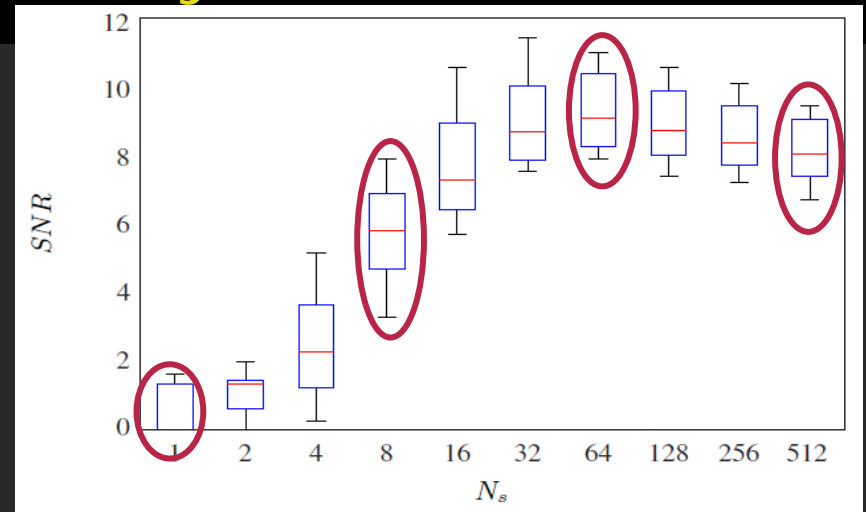
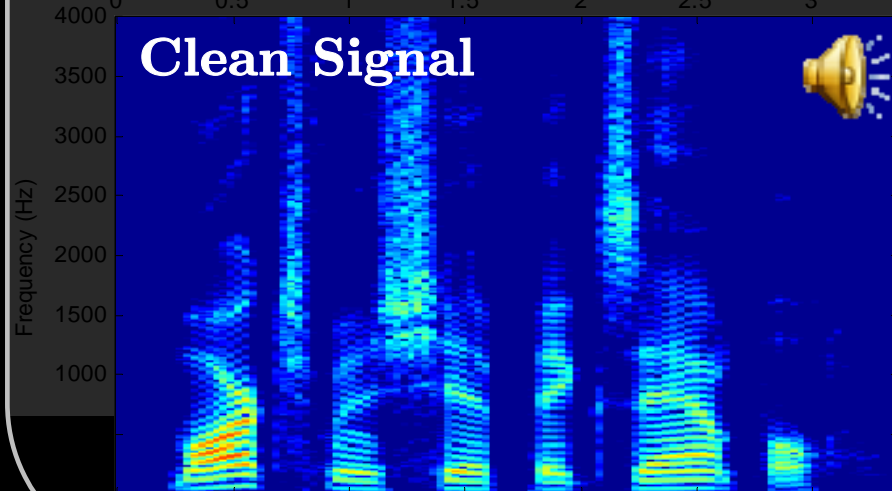
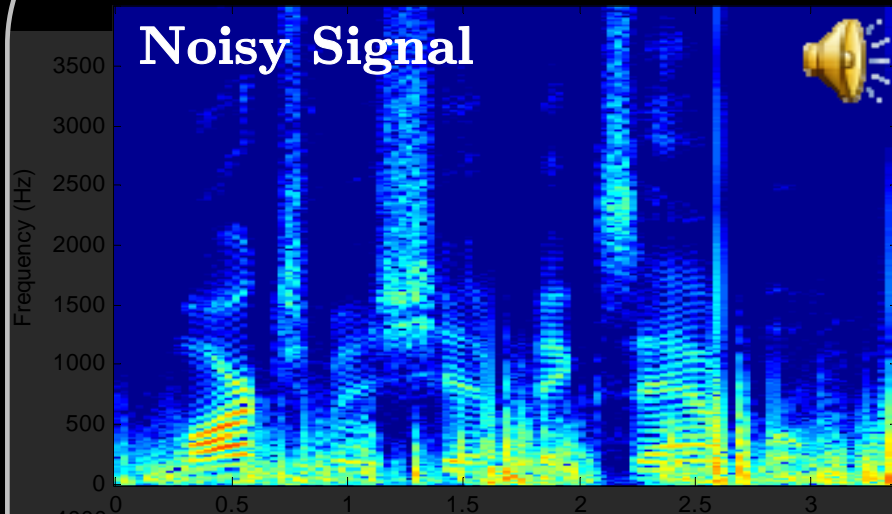


# Number of Noise-Dictionary Elements









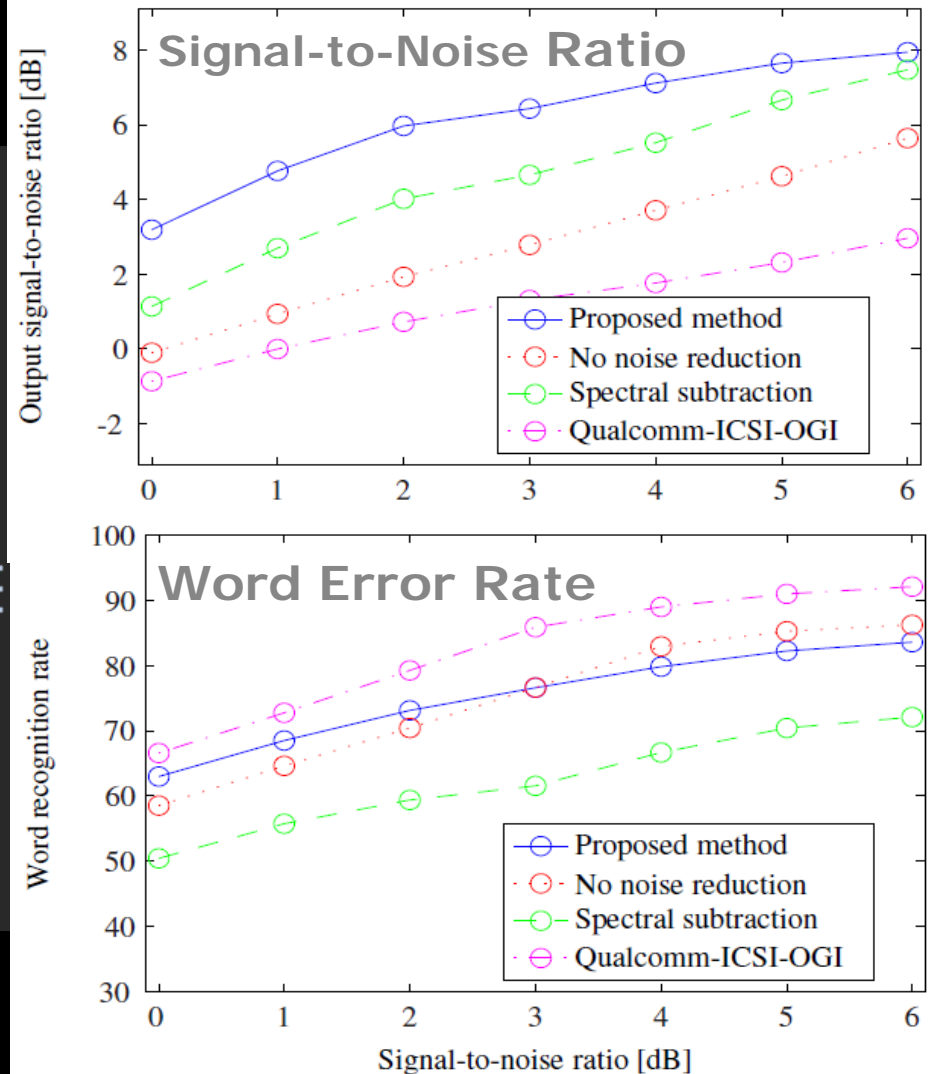
# Number of Speech-Dictionary Elements





# Comparison

- 1 Proposed method 
- 2 No noise reduction 
- 3 Spectral subtraction 
- 4 Qualcomm-ICSI-OGI aka adaptive Wiener filtering (Adami et al. 2002) 





## Conclusions and outlook

- Sparse coding of spectrogram representations is a useful tool for reduction of wind noise
  - Only samples of wind noise are required
- Careful evaluation and integration of perceptual measures
  - Handling nonlinear saturation effects
  - Optimization of performance (fewer freq. bands, adaptation to new situations)